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Questioni di Economia e Finanza
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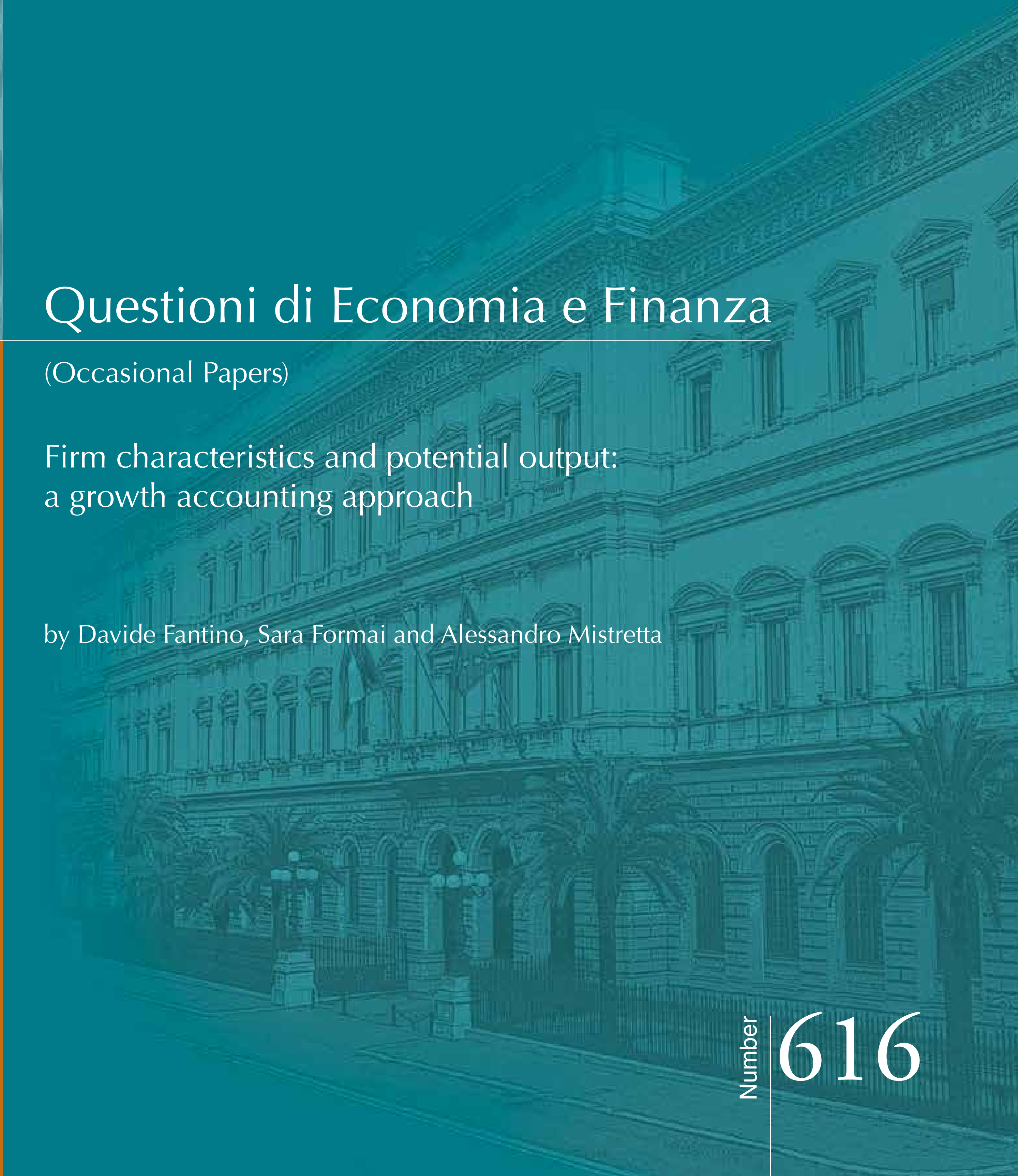

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FIRM CHARACTERISTICS AND POTENTIAL OUTPUT: A GROWTH ACCOUNTING APPROACH

by Davide Fantino*, Sara Formai* and Alessandro Mistretta*

Abstract

We apply a growth accounting approach to estimate the contribution to potential output growth in Italy by firms with different characteristics. We do so by exploiting time series obtained by aggregating individual firm data. Results show that during the double-dip recession smaller firms provided the strongest negative contribution to potential output growth, while the recovery was driven by big ones. Young firms always give a positive contribution. Growth within sectors is the main driver of the dynamic of both aggregate trend total factor productivity and the capital labor ratio. Looking at sectoral composition effects, between 2014 and 2018 sectors with lower capital deepening have increased their share in the economy, holding back the aggregate figures.

JEL Classification: D24, E23.
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1. Introduction[1]

The concepts of potential output and output gap are widely used by policymakers in their assessment of both the economic structure and the sustainability of growth in the medium and long-term. Short-run fluctuations of output are also significant and may have more prolonged impacts on both the level and the growth rate of potential output, especially when reflecting supply factor conditions such as changes in the availability of key production inputs and in productivity.. This was indeed the case for the recessive episodes of 2008 and 2012 (Mourougane, 2017) and a long-lasting impact can be expected for the COVID-19 crisis, unless policy interventions prove effective in limiting the losses and can sustain the recovery (Heimberger, 2020).

The traditional methodologies used to estimate potential output are based on aggregate time series, mainly the national accounts. The most popular methods adopted by international institutions and central banks are either statistical filters or more complex approaches, such as those based on aggregate production functions, on semi-structural Bayesian unobserved component methods, as well as on dynamic factor or dynamic stochastic general equilibrium models (see for example Havik *et al.*, 2014; De Masi, 1997; Alichi *et al.*, 2019; Edge and Rudd, 2016; Anderton *et al.*, 2014; Vetlov *et al.*, 2011; Chalaux and Guillemette, 2019; Bassanetti *et al.*, 2010; Busetti and Caivano, 2016; Burlon and D'Imperio, 2020).

While aggregate data are useful to obtain an overview of the state of the economy at a glance, they usually fail to capture the heterogeneity that exists among economic agents. This information can be crucial both to understand the main factors driving the growth of an economy and to address economic policies correctly. Fantino (2018) proposed a production function approach to assess potential output based on firm-level data. However, the assumptions behind this micro-based methodology are different from those required when using aggregate time series and the results are therefore not immediately comparable.

On the one hand, the standard aggregate data approaches use value added (instead of gross production) and two production factors (capital and labor), combined with a constant return to scale technology, ignoring the fact that intermediate inputs are another relevant choice variable at the firm level. More specifically, the use of value added as a measure of output assumes the stricter hypothesis that the underlying production function is additive-separable in value added and intermediate inputs;

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otherwise, in the evaluation of total factor productivity, the relationship between total factor productivity (TFP) improvements and intermediate goods may not be sufficiently taken into account (OECD, 2001). The micro approach instead allows us to estimate a gross production function on the three factors without imposing any prior constraints about the extent of the returns to scale.[2] Firm-level value added can then be obtained by simply subtracting the value of intermediate goods from gross production.[3] On the other hand, firm-level data may fall short in capturing macroeconomic slack, as they cannot incorporate the impact of systemic variables not having a firm-level counterpart. This is the case for demographic developments and the NAIRU, whose impact on firm-level potential output can only be measured through other observable firm-level variables such as firm entry and exit and long-run choices regarding capital investment and the hiring and firing of employees.

In this paper, we propose a measure of potential output that retains the rich information at the firm level, but at the same time follows assumptions and methodologies more consistent with the standard approaches based on aggregate data, typically included in the dashboard of policymakers and international institutions.[4]

In particular, we follow a growth accounting approach (Barro, 1999), where total factor productivity is estimated as a Solow residual from a Cobb-Douglas value added production function under the assumption of constant returns to scale, by using aggregate statistics retrieved from a very rich firm-level dataset in the time window between 2000 and 2018. The methodology is broadly similar to the production function approach to the potential output estimation used in several institutions, including the Bank of Italy (Bassanetti *et al.,* 2010).

The main source of information is firm balance sheets from Cerved/Centrale dei Bilanci, with the addition of data on employment from the National Social Security Institute (INPS), firm demography from the Italian Chamber of Commerce (Infocamere), and sectoral deflators and depreciation rates from the national accounts. We applied several methodological tools to ensure that our dataset is as representative as possible of aggregate output in the sectors of economic activity

[2] The micro-econometric literature has nevertheless often relied on a value added production function in estimating total factor productivity and input elasticities: see for instance the seminal contributions of Ackerberg *et al.* (2015) and De Loecker and Warzynski (2012) in their application to markups estimation. Nevertheless, the elasticities of a three-factor production function cannot be nested in the aggregate standard approaches because the constant returns to scale assumption is needed to calibrate the parameters of the standard Cobb Douglas formulation and so the micro-econometric panel-based techniques lose their theoretical pinning with aggregate time series.

[3] Moreover, the aggregate value added total factor productivity growth rate can be calculated as the sum of gross output disaggregated ones at firm or industry level, weighted by the nominal shares of gross output in total value added (see Domar, 1961; Gollop, 1987; and OECD, 2001 for further discussion).

[4] A comparison of our measure of potential output growth with those of the main international institutions is reported in Appendix B.

included in the dataset (i.e. the private sector excluding agriculture, mining, financial and real estate services).

To study the growth of potential output from firm-level data, we use two different aggregations: in the first one, we apply our methodology to time series obtained by directly aggregating firm-level data. In the second one (indirect aggregation) in order to study heterogeneity, we use two steps: first, we aggregate firms in homogenous groups according to a selection of their characteristics and calculate group-specific potential output series, and then we aggregate these with suitable weights. In this way, we perform several exercises in which we compute potential output separately for groups of homogeneous firms and identify the contribution of each group to aggregate potential growth. Last, in the spirit of Olley and Pakes (1996), we decompose the changes in aggregate total factor productivity and the capital labor ratio into the variation within each sector of economic activity and other variations due to changes over time in the sectoral composition.

The rest of the paper is organized as follows. Section 2 describes the characteristics of our dataset and discusses whether it is representative of the dynamics of aggregate value added for the sectors of the Italian economy included in the dataset (the private sector excluding agriculture, mining, financial and real estate services). In Section 3 we explain the methodology we used to estimate potential output. Section 4 presents the main findings of our analysis. Section 5 deepens the analysis by sector of economic activity to study the role of sectoral composition in driving the aggregate dynamics of trend total factor productivity and the capital labor ratio. In Section 6 we discuss several methodological robustness checks for the aggregate dynamics of potential output. Finally, Section 7 concludes.

2. Data

We constructed our dataset using balance sheets from the Company Accounts Data System from Cerved/Centrale dei Bilanci, which includes yearly information about virtually all the Italian non-financial limited liability companies; smaller firms such as partnerships are not included. For each firm, we extracted from Cerved the book value amount of physical and immaterial capital, value added, revenues, cost of labor, depreciation, investments and divestments, the expenditure in intermediate goods and services, the sector of economic activity according to the Ateco classification (2 digits; ISTAT, 2009).

We deflated all nominal variables using the relevant ISTAT national account deflators for each economic sector; from this source, we also retrieved the sectoral statistics relating to capital depreciation. We collected additional information about firm employment from the archives of INPS and data on birth, death, mergers and acquisitions of firms from the Infocamere database.[5]

We performed some adjustments to the raw data to improve the coverage and the quality of the dataset. In detail, we dropped firms with gaps of more than three consecutive years in a relevant variable, while we filled smaller gaps by linear interpolation.[6] Moreover, for each year and sector of economic activity, we winsorized the first and the last 5% of the distribution of the ratio between investments and assets and of the growth rate of any other continuous variable.

The real capital (K_{it}^{PI}) of firm *i* at time *t* has been computed applying the permanent inventory methodology (OECD, 2009): for each firm we cumulated real investment I_{it}, net of firm-level divestment rate (σ_{it}) and of sector-level (s) capital depreciation rate (δ_{st}):

$$K_{it}^{PI} = (1 - \delta_{st}) * (1 - \sigma_{it}) * K_{it-1}^{PI} + I_{it}.$$

The permanent inventory methodology is usually preferred to the direct use of the book value capital in the balance sheet, as it is not plagued by biases deriving from the depreciation or re-evaluation policies of each firm.[7]

National accounts define sectoral depreciation as the share of value lost by physical capital during the year due to wear and tear, obsolescence and accidental damage; with this definition, capital older than a threshold age is assumed to be dismissed. To avoid partial double accounting in the calculation of the permanent inventory capital between sectoral depreciation and firm-level divestments, in a robustness check we also use an alternative, more conservative, formulation of the permanent inventory methodology where real capital K_{it}^{PI2} is calculated at the gross of divestments:

$$K_{it}^{PI2} = (1 - \delta_{st}) * K_{it-1}^{PI2} + I_{it}. \quad (1)$$

Firms operating in the agricultural, mining, financial, real estate services, broad public and household services sectors are not included because their sample in the Cerved dataset is not representative, and their dynamics cannot be modelled by a production function methodology due to

[5] Firms entering the sample after 1995 or exiting before 2018 have been included in the dataset only if respectively their first or last balance sheet was near the birth or death date declared in Infocamere.
[6] We imputed an isolated missing value within the time series using the average of the two values in the previous and in the following periods; in the case there were two or three consecutive missing values, we imputed them using a linear function between the previous and following non-missing data.
[7] Unless the whole history of investments of a firm is available, the initial amount of capital when using the permanent inventory methodology is approximated by the deflated book value of capital. To minimize possible biases in the initial years of the dataset we used all the available investment data from 1995 to construct capital, but we only observe potential output in the time window between 2000 and 2018. In a robustness check, the amount of capital for each firm has been rescaled in 1995 in such a way that the shares of capital in each sector in our sample exactly mimic those reported in the national accounts; the inclusion of this additional correction does not change the results.

sectoral peculiarities.[8] The sectors of economic activity included in our dataset cover about 60% of the overall value added of the Italian economy. We reclassified the Ateco sectors of the remaining firms according to the intermediate aggregation Sna/Isic in 38 categories for manufacturing and to the aggregation in 11 categories for the other sectors (ISTAT, 2009).

Table 1 – Descriptive statistics

	Unweighted					Weighted		
	Mean	S.d.	Min	Median	Max	Mean	S.d.	Median
Real sales	6,010.17	387,843.76	-	709.14	400,200,000	2,744.69	220,238.63	498.28
Real purchases of goods and services	4,103.50	82,601.65	-	483.70	44,329,452	1,965.28	47,742.35	343.76
Real value added	1,002.83	23,712.42	-1,091,954	151.43	10,069,198	446.17	14,065.78	106.00
Number of workers	17.46	384.77	0.08	4.89	530,673	8.63	217.25	3.67
Cost of labor	707.82	12,299.80	0.01	135.00	5,826,142	322.32	7,339.01	91.00
Real net immaterial assets (BV)	271.39	26,313.17	-	3.41	18,142,360	112.32	16,133.55	2.73
Real net immaterial assets (PI)	431.08	19,187.59	-	11.18	9,038,922	182.49	11,448.20	7.65
Real net immaterial assets (PI2)	489.66	21,108.41	-	12.46	9,109,466	206.87	12,520.96	8.45
Real net material assets (BV)	1,514.79	126,960.88	-	51.07	89,388,768	652.20	71,927.14	39.15
Real net material assets (PI)	1,909.01	83,016.02	-	112.16	42,178,000	841.37	48,011.75	84.56
Real net material assets (PI2)	2,224.60	96,923.35	-	127.56	47,751,188	975.97	55,801.10	95.44
Real total net fixed assets (BV)	1,786.17	132,318.66	0.01	71.81	89,389,240	764.51	75,334.96	55.13
Real total net fixed assets (PI)	2,340.09	90,824.08	0.01	155.72	43,047,900	1,023.86	52,775.97	117.09
Real total net fixed assets (PI2)	2,714.27	104,943.70	0.01	175.80	48,978,004	1,182.84	60,666.74	131.45
Nominal total net fixed assets (PI)	2,151.07	83,585.58	0.01	143.09	37,910,330	939.56	48,644.14	106.52
Real gross immaterial investments	53.35	3,158.57	-	-	2,552,431	23.93	1,904.16	-
Real gross material investments	206.13	8,914.48	-	5.97	11,375,091	93.61	5,245.07	4.02
Real divestments	55.99	9,259.37	-	-	20,709,184	24.83	5,217.53	-
Age of firm	14.23	12.10	1.00	11.00	119	12.60	10.99	9.00

The dataset includes 7142613 observations regarding 995259 firms between 2000 and 2018. All the values, except number of workers (average monthly units per year), the capital labor ratio and the age of firm, are in thousand euros. All the real variables are chain linked values with basis 2015. BV: book value; PI: permanent inventory method; PI2: permanent inventory method without using firm level divestments.

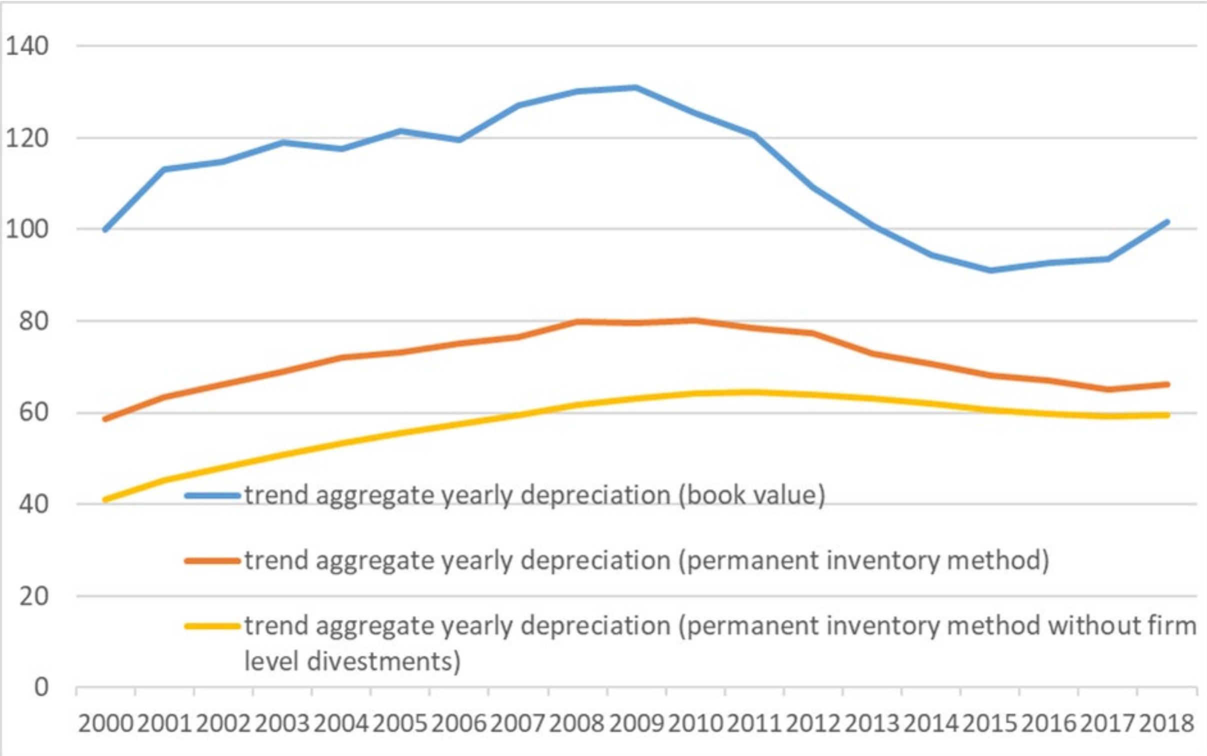
The final dataset includes 7.1 million observations, corresponding to about slightly less than one million firms between 2000 and 2018. The left panel of Table 1 shows the descriptive statistics of the dataset. The average firm is 14 years old, it has about 6 million euros of turnover, 1 million of value added, 17 employees and about 2 million euros of net fixed assets. Most of the variables from the balance sheet are skewed to the right. The amount of both material and immaterial net assets stated in the balance sheets are generally smaller than those built using the standard permanent inventory method, as the average depreciation rates deduced from the balance sheets are bigger than those implied by the national accounts.

Figure 1 compares the levels and the dynamics of trend (5-year moving average) aggregate depreciation and divestment of the firms in the dataset for the three different definitions of capital; values are normalized using the book value amount in 2000 as a reference. Yearly book value

[8] The excluded sectors (agriculture, mining, financial, real estate services, broad public and household services sectors) correspond to Ateco 2007 codes smaller than 10, between 64 and 68 and bigger than 82.

depreciation is more cyclical and it is almost twice that implied by the permanent inventory method. When considering the two alternative formulations of this last method, we see that firm-level divestments account for about one third of the overall amount of depreciation in 2000, but their share declines over time and becomes less than one sixth in 2018. The two cases are respectively a lower and an upper bound of the likely true value of aggregate depreciation and divestment. We obtain the same qualitative results when repeating this analysis for each sector of economic activity.

Figure 1 – Trend depreciation and divestment of capital



Since Cerved includes mostly limited liability companies, its coverage is biased in favor of larger firms. As to improve the representativeness of the dataset, the best we can do is to use statistics on the universe of Italian firms with strictly positive employees in the INPS archives to create a system of weights. We considered cells defined in terms of year, sector, geographic area[9] and class of number of employees[10] and we weight each firm in our dataset by the ratio between the number of firms belonging to its cell reported in INPS and the one in our sample. We report the descriptive statistics of the weighted dataset in the right panel of Table 1: the general characteristics of the dataset

[9] We used 4 macro-areas: North-West, North-East, Centre and South including Islands.

[10] We segmented the distribution of employees in four classes: up to 10, between 11 and 20, between 21 and 100 and more than 100 employees.

remain broadly unaltered, but the skewness of the relevant variables is smaller and the weight of smaller firms increases.[11]

Figure 2 – Aggregate real value added in national accounts and Cerved

The aggregate dynamics of unweighted and weighted real valued added of the firms in the dataset are presented in Figure 2 and compared with that from national accounts, obtained by summing up the series for the same sectors of economic activity.[12] We also show the dynamics of real GDP in the same years as a reference. Because Cerved firms cover most of the output of the total economy, the representativeness of the raw data is already good, in particular after 2008, but when the weights are used the dynamics of value added get even closer to that of national accounts.[13]

[11] This outcome is precisely in the spirit to overcome some of the limitation in the representativeness of the Cerved database. Anyway, a possible drawback of this ponderation is that the smallest Cerved firms, which weight is substantially increased, might not be representative of (and might be better than) the average smallest firms, mainly partnerships, included in INPS, which anyway already excludes those with no employees. In order to have some hints about the magnitude of the possible distortion that our correction might imply, we compared the average value added of each cell for the smallest firms in Cerved with the similar ones from Siam, a dataset of partnerships having relationships with banks including about 100,000 minor firms. The comparison corroborates the good quality of our dataset, as the distribution of the average value added by cell is very similar in the two datasets and there is no sign that the distribution of the Cerved firms is shifted towards a bigger size.

[12] The temporary interruption of the recovery in 2016 is due to the sector of utilities (D-E; see Figure A1 in Appendix A), whose dynamics is strongly affected by regulation and non-market factors.

[13] The same comparison studying the dynamics of the aggregated overall gross production of firms gives broadly similar results.

Table 2 – Trend sectoral income shares of labor in Cerved and in national accounts

Source	Year	Sectors						
		Manufacturing (C)	Utilities (D-E)	Construction (F)	Wholesale and retail trade, transportation and storage, accommodation and food service activities (G-H-I)	Information and communication services (J)	Professional, scientific, technical, administration and support service activities (M-N)	All sectors (C-D-E-F-G-H-I-J-M-N)
National accounts	2000-2018	0.66	0.37	0.78	0.70	0.52	0.69	0.68
Cerved	2000-2018	0.65	0.34	0.70	0.68	0.60	0.72	0.65
	2000	0.61	0.42	0.65	0.64	0.61	0.67	0.62
	2001	0.62	0.41	0.66	0.65	0.61	0.69	0.63
	2002	0.62	0.40	0.66	0.65	0.61	0.71	0.63
	2003	0.63	0.39	0.66	0.66	0.59	0.71	0.64
	2004	0.64	0.39	0.67	0.67	0.58	0.72	0.64
	2005	0.63	0.38	0.67	0.68	0.58	0.71	0.64
	2006	0.64	0.37	0.66	0.68	0.58	0.71	0.64
	2007	0.65	0.37	0.66	0.69	0.58	0.72	0.65
	2008	0.66	0.36	0.67	0.69	0.59	0.72	0.66
	2009	0.67	0.34	0.68	0.70	0.59	0.72	0.66
	2010	0.69	0.33	0.70	0.71	0.60	0.73	0.68
	2011	0.69	0.32	0.72	0.72	0.61	0.74	0.68
	2012	0.69	0.31	0.74	0.71	0.62	0.74	0.68
	2013	0.69	0.30	0.74	0.71	0.62	0.74	0.68
	2014	0.68	0.29	0.75	0.70	0.63	0.74	0.68
	2015	0.67	0.29	0.74	0.69	0.62	0.74	0.67
	2016	0.66	0.29	0.74	0.68	0.62	0.74	0.66
	2017	0.65	0.28	0.73	0.68	0.61	0.74	0.65
	2018	0.65	0.28	0.73	0.68	0.61	0.74	0.65

Note: annual values are 5 years centered moving averages, with the exception of 2017 (3 years centered moving average) and 2018 (raw value).

Finally, Table 2 shows the income shares of labor, calculated over the nominal value added, by sector of economic activity in our dataset and according to the national accounts.[14] The overall share for the sectors included in our analysis using sample data is 0.65, marginally lower than the corresponding one in the national accounts for the same sectors (0.68). As a reference, the value from the national accounts for the whole economy is 0.62. The heterogeneity by sector is potentially relevant:[15] the sectors 'construction' (F), 'trade, transportation, accommodation and food services' (G-H-I) and 'professional, administrative and support services' (M-N) are more labor intensive than the average; 'manufacturing' (C) follows, while 'utilities' (D-E) and the other segments of services show smaller shares.

The bottom half of the table shows the trend labor shares in our sample. We use these time-varying values in a robustness check. We calculate trend labor shares as a centered 5-year moving averages of the raw shares to minimize their cyclical fluctuations, which should not be captured by

[14] Using a standard procedure, the value for the national accounts is calculated using the hourly income of dependent employees as a proxy for the one of independent workers.
[15] Here for sake of brevity we do not show the values for the specific segments of manufacturing, but their heterogeneity is taken into account in the analysis.

potential output.[16] There is some variability over time: the share increases in almost all sectors between 2000 and 2018, with the exception of 'utilities', where it decreases, and of 'communication services' (J), where it is strongly cyclical; it increases among manufacturing firms until 2011 and slightly decreases afterwards.[17]

3. Methodology

We apply a growth accounting approach to estimate aggregate potential output dynamics from the Cerved firm-level dataset and to draw information on its main drivers. Total factor productivity (TFP) is estimated as a Solow residual from a Cobb-Douglas production function applied to the directly or indirectly aggregated time series of the dataset under the assumption of constant returns to scale, which implies that the elasticities of the primary production factors (capital and labor) are equal to the share of their returns over the output. Then we obtain the trend components of TFP and labor using a Hodrick-Prescott filter, while for capital we use historical data. Finally, we construct potential output by combining the trend components of inputs and of TFP through the Cobb-Douglas production function.

More in detail, when using our approach on the directly aggregated time series[18] we start from a two-factor fully aggregate production function

$$\mathrm{Y}_t = \mathrm{TFP}_t\ \mathrm{F}(\mathrm{K}_t, \mathrm{L}_t) = \mathrm{TFP}_t\ \mathrm{K}_t^{1-\alpha}\mathrm{L}_t^{\alpha} \tag{2}$$

where Y_t is the measure at time *t* of value added, K_t of capital, L_t of the number of workers, obtained by aggregation of firm-level data; TFP_t is the level of technology, defining the total factor productivity. By totally differentiating, we obtain the following growth identity:

$$\frac{\Delta \mathrm{Y}_t}{\mathrm{Y}_{t-1}} = \frac{\Delta \mathrm{TFP}_t}{\mathrm{TFP}_{t-1}} + (1-\alpha)\frac{\Delta \mathrm{K}_t}{\mathrm{K}_{t-1}} + \alpha\frac{\Delta \mathrm{L}_t}{\mathrm{L}_{t-1}}.$$

Assuming that the factors of production are paid for their marginal product under profit maximization, α and $(1-\alpha)$ are equal, respectively, to the shares of labor and capital income over nominal value added. The value of the former is set according to the average value of the share in our

[16] The values reported for 2017 are 3 years moving averages, while those for 2018 are not averaged at all.
[17] This evolution of the labour share in Italy, as well as in some other European countries, is in sharp contrast with the declining labour share observed for the U.S. and that has been extensively studied by the literature (see for instance Autor *et al.*, 2020 and Acemoglu and Restrepo, 2018).
[18] The methodology used for the directly aggregated time series is a modified version of the ones for aggregate time series used in Bassanetti *et al.* (2010) and in the creation of the official time series of potential output of the Bank of Italy. The modifications here introduced are needed to take into account the peculiarities of the firm-level data and heterogeneity.

sample in the whole time window for all the considered sectors of economic activity, already shown in Table 2 and equal to 0.65.[19] Hence, the latter is set to 0.35.

Total factor productivity growth can be therefore retrieved as a residual:

$$\frac{\Delta \mathrm{TFP}_t}{\mathrm{TFP}_{t-1}} = \frac{\Delta \mathrm{Y}_t}{\mathrm{Y}_{t-1}} - \left((1-\alpha)\frac{\Delta \mathrm{K}_t}{\mathrm{K}_{t-1}} + \alpha \frac{\Delta \mathrm{L}_t}{\mathrm{L}_{t-1}} \right).$$

In our exercise, we use the log transformation of equation (2) to obtain the log level of TFP

$$\mathrm{tfp}_t \equiv \log(\mathrm{TFP}_t) = \log\left(\frac{\mathrm{Y}_t}{K_t^{1-\alpha} L_t^{\alpha}}\right)$$

and we extract its trend component ($tfp_{HP,t}$) using a Hodrick Prescott filter with parameter 100. We apply the same procedure to the log of the input L_t to obtain the trend component $l_{HP,t}$. We do not filter capital, as it is less influenced by the economic cycle.[20]

We then calculate potential output as

$$\log \widetilde{\mathrm{Y}}_t = tfp_{HP,t} + (1-\alpha)\log(K_t) + \alpha l_{HP,t} \equiv \log\left(TFP_{HP,t} K_t^{1-\alpha} L_{HP,t}^{\alpha}\right) \tag{3}$$

where lower case letters are used for logs and capital letters for not transformed levels. Equation (3) implies, after differentiation,

$$\frac{\Delta \widetilde{\mathrm{Y}}_t}{\widetilde{\mathrm{Y}}_{t-1}} = \frac{\Delta \mathrm{TFP}_{\mathrm{HP,t}}}{\mathrm{TFP}_{\mathrm{HP,t-1}}} + (1-\alpha)\frac{\Delta \mathrm{K}_t}{\mathrm{K}_{t-1}} + \alpha \frac{\Delta \mathrm{L}_{\mathrm{HP,t}}}{\mathrm{L}_{\mathrm{HP,t-1}}} \equiv CI_{TFP,t} + CI_{K,t} + CI_{L,t}.$$

In this way, we can decompose potential output growth in the different contributions of inputs ($CI_{TFP,t}, CI_{K,t}, CI_{L,t}$).

When we use our approach on the indirectly aggregated time series, we repeat the same exercise on subsets of firms, aggregating the firm-level dataset in different categories according to the firm characteristics of interest (e.g. sector of activity, size, age, location, etc.). The partially aggregated potential output $\widetilde{\mathrm{Y}}_{i,t}$ for each subset *i* of firms will be

$$\log \widetilde{\mathrm{Y}}_{i,t} = tfp_{HP,i,t} + (1-\alpha_i)\log K_{i,t} + \alpha_i l_{HP,i,t}$$

where all the variables indexed by *i* are the same as in the equation (3), but they are now referred to a specific subset of firms. The shares of labor income α_i used here are the averages for that group of

[19] We use a time-varying version of the shares in a robustness check; even if we tried to capture trend behavior using a 5-year moving average, potential output dynamics become too much cyclical.

[20] Filtering investments, the relevant choice variable of firms for capital, increases the smoothness of the estimates of potential output growth; we use the actual capital in line with the methodological choices of the main international institutions (see Appendix B). Using trend investments instead of the actual ones would not qualitatively change the results of the analysis.

firms, where sector-level shares assigned to each firm are weighted using nominal value added. We assume once again constant returns to scale; hence, the capital income share is $(1-\alpha_i)$. In this case, aggregate potential output for all firms $\widetilde{\mathrm{Y}}_t$ is the sum of partially aggregated potential outputs calculated for each subset of firms:

$$\widetilde{\mathrm{Y}}_t = \Sigma_i \widetilde{\mathrm{Y}}_{i,t},$$

implying that the overall potential output growth can be decomposed in the contributions $CC_{i,t}$ of the firms from each subset of firms, each calculated as the potential output growth rate of the subset multiplied by the its share of aggregate potential output in the previous period (w_{it-1}):

$$\frac{\Delta\widetilde{\mathrm{Y}}_t}{\widetilde{\mathrm{Y}}_{t-1}} = \Sigma_i \frac{\tilde{Y}_{i,t-1}}{\widetilde{\mathrm{Y}}_{t-1}} \frac{\Delta\tilde{Y}_{i,t}}{\tilde{Y}_{i,t-1}} = \sum_i w_{i,t-1} \frac{\Delta\tilde{Y}_{i,t}}{\tilde{Y}_{i,t-1}} \equiv \Sigma_i CC_{i,t}. \tag{4}$$

Last, in a robustness check, we use the Tornqvist index methodology[21] in the calculation of the potential output; in this case, the dynamics of the index follow:

$$\Delta \log \widetilde{\mathrm{Y}}_t^T = \Sigma_i \frac{1}{2}\left(\frac{\widetilde{\mathrm{P}}_{i,t-1}\widetilde{\mathrm{Y}}_{i,t-1}}{\widetilde{\mathrm{P}}_{t-1}\widetilde{\mathrm{Y}}_{t-1}} + \frac{\widetilde{\mathrm{P}}_{i,t}\widetilde{\mathrm{Y}}_{i,t}}{\widetilde{\mathrm{P}}_t\widetilde{\mathrm{Y}}_t}\right) \Delta \log \widetilde{\mathrm{Y}}_{i,t} = \sum_i w_{i,t}^T \Delta \log \widetilde{\mathrm{Y}}_{i,t} \tag{5}$$

where $\widetilde{\mathrm{P}}_{i,t}$ and $\widetilde{\mathrm{P}}_t$ are respectively the sectoral and aggregate filtered value added price indexes.

The evaluation of the dynamics of potential output in the exercises presented here is subject to the caveats, discussed in the introduction, about the use of a two-factors production function with constant returns to scale and the difficulty in capturing the effects of the macroeconomic slack with firm-level data. Moreover, a drawback of the mixed methodology used here is that, due to the non-linearity of the production function, the dynamics of potential output depend on the degree of aggregation of the time series.[22] In particular, the growth rates calculated aggregating potential output of groups of firms can differ depending on the firm characteristic used to split the sample, and they can differ from the one calculated using the directly aggregated time series. The reason is that when aggregating time series we lose relevant information about the heterogeneity in the distribution of inputs among firms. Anyway, from the comparison of the overall dynamics shown in the next section for the different cases we can conclude that the differences are never so strong to qualitatively affect our assessment.

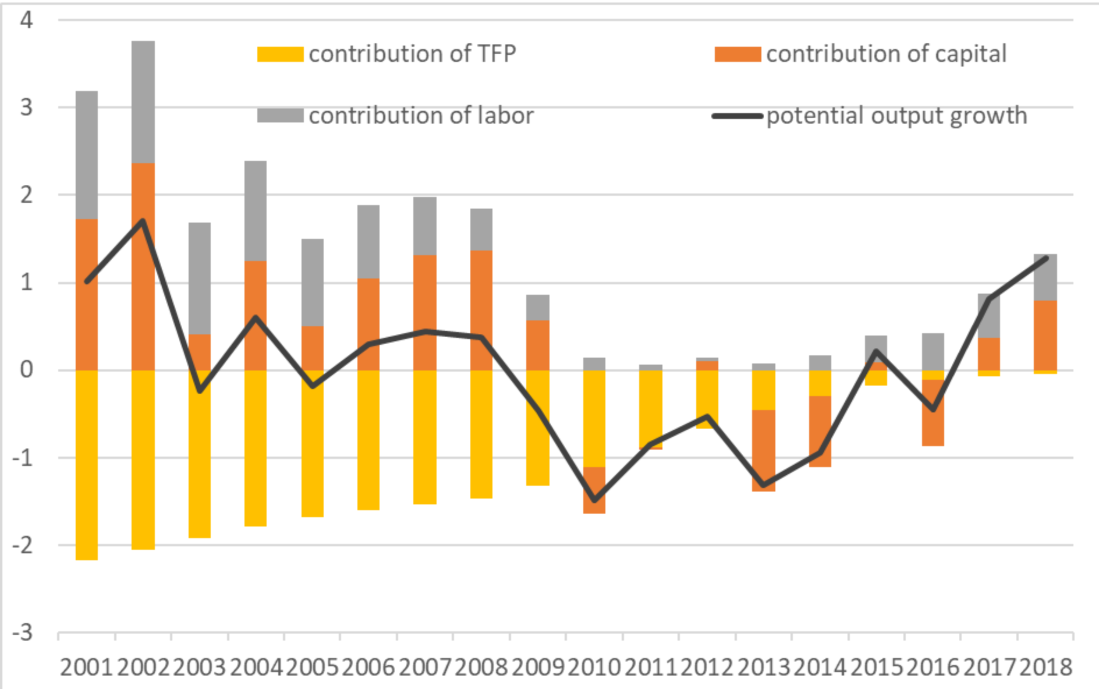
[21] The Tornqvist index is the discrete time version of the Divisia index, which according to the literature has many desirable properties, even if it has some serious drawbacks (Hulten, 1973); for this reason, it is used in studies analysing productivity changes (OECD, 2001).

[22] This drawback is a clue that, in presence of a non-linear production function, methods using aggregate data neglect the distribution of inputs among firms which turns to be relevant when aggregating firm-level production functions.

4. Main results

In this section, we show the results of the different exercises of aggregation made possible by our rich sample. In the first one, we study the overall dynamics of potential output based on directly aggregated time series (Figure 3).[23] Three different periods can be clearly distinguished: 1) the pre-crisis period (2001-08), with an average potential output growth of about 0.5% per year; 2) the period 2009-14, when potential output decreased on average by about 0.9% per year; 3) the post-crisis period (2015-18), when the average growth turns back to about 0.5% per year.

Figure 3 – Potential output growth, input contributions



Before the recessions, potential output growth is mainly supported by capital and labor. During the recessions, contribution of capital is almost always negative, as investments drop dramatically and replacement is not enough to compensate depreciation, while that of labor is negligible. Afterwards, labor first and then also capital start providing again a positive support to output growth, in part thanks to public incentives to private investments. Total factor productivity, whose dynamic is sluggish and lower in the international comparison from the mid-90s, is a drag to growth at the beginning of our sample but its dynamics gradually improves.

[23] We use the estimates based on the directly aggregated dataset as a benchmark instead of those that use the indirectly aggregated ones because the former are methodologically nearer to the traditional aggregate methods.

In the next exercises, we use the granular information to partition the dataset in homogeneous groups according to different firms' characteristics (such as sector of economic activity, size, age, and geographic location; additional decompositions are reported in Appendix A), and then we build time series by aggregating firms belonging to these groups. In this way, we are able to evaluate whether some specific groups of firms drive potential output dynamics.

Table 3 – Potential output growth, industry shares and growth rates

Sectors		average growth rate					share	
		2001-2004	2005-2008	2009-2013	2014-2018	2001-2018	2000	2018
Manufacturing of	food (CA)	1.84%	1.85%	2.03%	0.63%	1.56%	3.80%	5.01%
	texile (CB)	-4.48%	-2.96%	-0.85%	1.43%	-1.49%	4.87%	3.69%
	wood & paper (CC)	-1.83%	-1.24%	-2.29%	-1.06%	-1.61%	2.71%	2.02%
	coke & petroleum (CD)	-8.30%	-10.98%	-19.62%	-22.21%	-15.91%	1.47%	0.06%
	chemicals & pharmaceuticals (CE-CF)	1.10%	-0.68%	0.05%	1.75%	0.59%	2.61%	2.90%
	rubber & plastics (CG)	0.29%	-1.39%	-2.27%	0.02%	-0.87%	3.85%	3.29%
	basic metals (CH)	1.09%	1.02%	-0.38%	2.42%	1.04%	4.68%	5.62%
	electronic equipment (CI)	0.38%	-2.06%	-3.92%	-1.15%	-1.78%	1.40%	1.01%
	electrical equipment (CJ)	-0.19%	-2.97%	-3.63%	-2.48%	-2.40%	2.14%	1.38%
	other machinery (CK)	0.26%	1.57%	0.71%	1.32%	0.97%	4.25%	5.05%
	transport (CL)	-1.79%	-1.31%	-1.66%	1.22%	-0.81%	2.13%	1.84%
	other products (CM)	-2.07%	-2.39%	-2.84%	-1.90%	-2.31%	5.28%	3.47%
Utilities (D-E)		2.49%	-1.76%	-0.91%	-1.23%	-0.43%	7.13%	6.53%
Construction (F)		0.09%	-1.32%	-6.47%	-4.17%	-3.23%	13.59%	7.46%
Wholesale and retail trade, transportation and storage, accommodation and food service activities (G-H-I)		2.19%	2.01%	0.99%	1.53%	1.63%	25.89%	34.61%
Information and communication services (J)		4.03%	0.74%	0.19%	-0.77%	0.90%	4.14%	4.79%
Professional, scientific, technical, administration and support service activities (M-N)		0.21%	1.81%	-0.51%	1.26%	0.66%	10.05%	11.29%
All sectors		0.63%	0.15%	-0.93%	0.34%	0.01%	100.00%	100.00%

As a first analysis, we study the growth of sectoral potential output and relates it to the variation in the output shares of the different sectors. Table 3 shows the average growth rates of potential output for the sectors of economic activity in the whole time window and in four sub-periods (2001-04, 2005-08, 2009-13, 2014-18) and the shares of sectoral potential output over the total at the start and at the end of the time window.

Between 2000 and 2018 the share of manufacturing firms decreased from about 40% to one third, following the slow process of gradual expansion of the services industry in the economy and the increased competition on international markets. Services play an important role to sustain potential output dynamics between 2001 and their share rose from 40% to one half; that of construction halved from about 13% in 2000.

Within the manufacturing sector, on the one hand, segments producing food and beverages (CA) and basic metals (CH) consistently increase their share; chemicals and pharmaceuticals (CE-CF) and other machinery (CK) also expanded. On the other hand, the weight of firms producing coke and refined petroleum products (CD), electronic (CI) and electric (CJ) equipment, textiles (CB) and wood and paper (CC) consistently shrank.

Within services, all segments significantly expanded and in particular ‘wholesale and retail trade, transportation and storage, accommodation and food service activities’ (G-H-I). ‘Professional, scientific, technical, administration and support services activities’ (M-N) also gave a positive contribution, while growth in ‘information and communication services’ (J) since the double-dip crisis slowed down and then halted.

The elaborations reported in Appendix A show some additional results, confirming this sectoral analysis: the most important drivers of potential growth are low capital-intensive, low knowledge-intensive sectors, while the contribution of high tech services is generally positive, but smaller.

Figure 4 – Potential output growth, by firm size

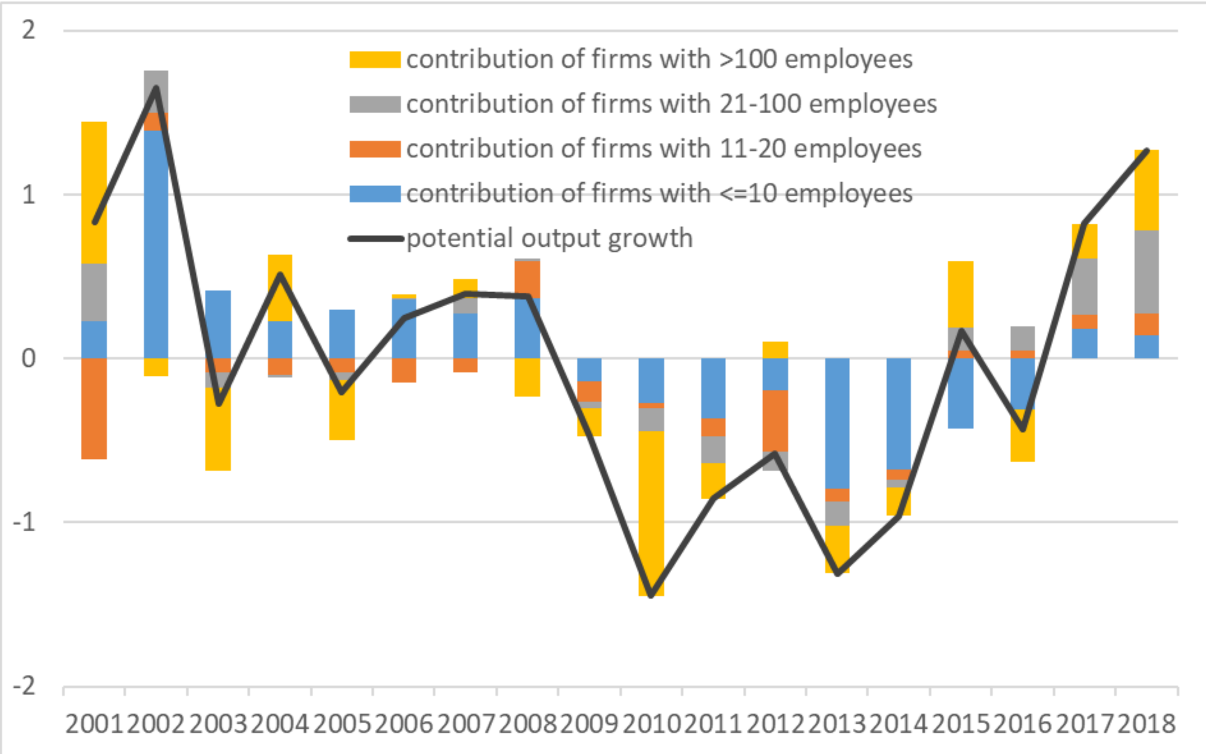
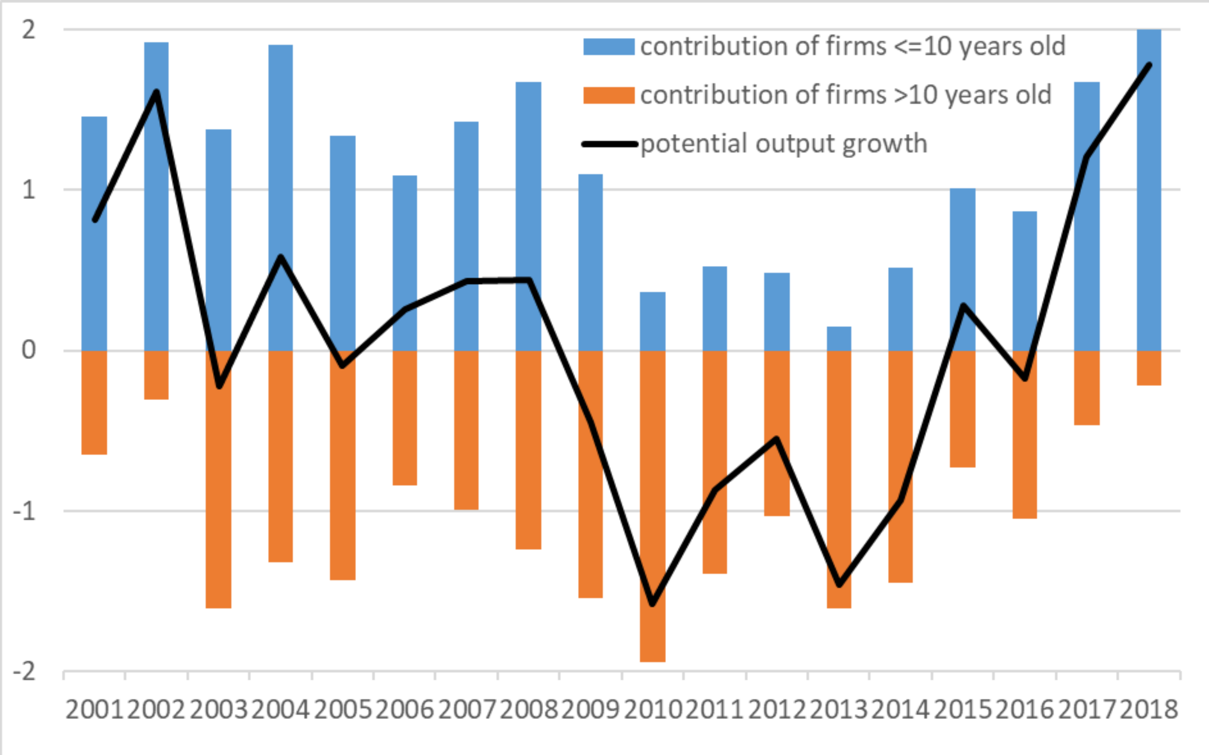


Figure 4 shows the contributions by firm size. We split the dataset in four different groups, respectively including firms with up to 10, between 11 and 20, between 21 and 100 and with more than 100 employees. Smallest firms, which in our sample account on average for 30% of overall potential output, are the main contributors to growth in most years. Their dynamics is slightly more positive than the other groups before the crisis, but, during the sovereign debt crisis, due to their structural weaknesses (see Bugamelli *et al.*, 2018), they were severely hit by the contraction in demand and the credit crunch and their negative contribution is more persistent and accentuated.[24] The contribution of the largest firms is also relevant, especially during the 2008-09 global crisis and in the more recent recovery.

Figure 5 – Potential output growth, by firm age



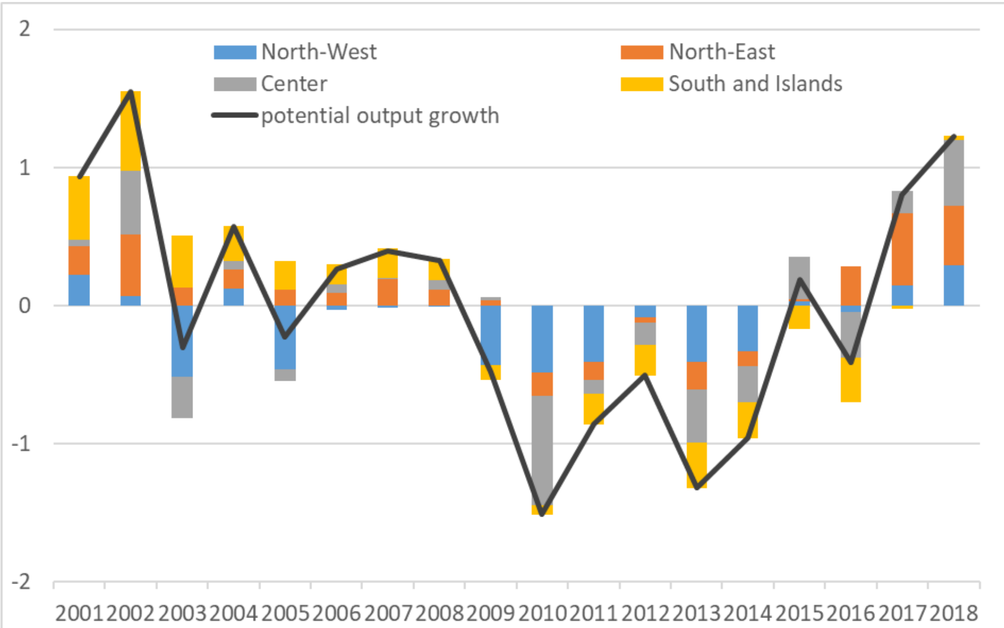
Furthermore, we investigate the contributions to potential output growth when splitting the dataset according to firms' age. We categorize the average age reached by a firm in the period of analysis in two groups, including respectively those up to 10 and more than 10 years old.[25] We find that younger firms are the main contributors to potential output growth, despite their average smaller size (Figure 5). Older firms give a negative contribution for the whole period. These results are is in line with the literature that shows the relevance of start-ups as drivers of economic growth and with previous evidence on Italian firms, which tend to grow old and small without being selected out of the market (Manaresi, 2015).

Finally, we split the sample according to the geographical area where firms are located. We use the standard classification of Italian regions in four macro-areas (North-West, North-East, Centre,

[24] The important and positive contribution of small firms in the first part of the sample might in part reflect the fact, as discussed in the introduction, this group of firms in Cerved could be better than those in the overall economy. This interpretation would be in contrast with their relevant and negative contribution in the 2009-14 period.
[25] The choice of the average age is required to keep the composition of groups constant over the period.

South with Islands). As shown in Figure 6, the dynamics of potential output is overall consistent across the different groups. The slowdown of potential growth in 2003 and 2005 and during the double-dip crisis is mainly related to the weakening of contributions of firms located in the North-West and in the Centre. The recovery in the more recent years gradually concerns all the geographical areas, even if the contribution of the South with Islands is weak; instead, it is particularly robust in the North-East.

Figure 6 – Potential output growth, by geographic location



5. Sectoral growth dynamics and composition

In this section, we study whether the dynamics of the inputs observed in the aggregate data are due to changes either within different sectors or in the structure of the economy over time.

We decompose a measure of aggregate trend TFP growth and the change in the aggregate ratio between capital and filtered labor in different components: a first one capturing the change due to variations at the sectoral level (within component), and a second one capturing the change due to the sectoral composition (reallocation component). The last one further reflects whether the sectors that have been expanding their share in the economy are also those with higher initial TFP or capital labor ratio (the so called 'between' term) and whether there has been a joint change in the sector share and in the TFP measure or capital labor ratio (cross term).

In detail, the aggregate ratio between capital and filtered labor (x_t^{KL}) can be obtained as the weighted sum of its sector-level counterparts ($x_{i,t}^{KL}$):

$$x_t^{KL} \equiv \frac{K_t}{L_{HP,t}} = \frac{\sum_i K_{i,t}}{\mathrm{L}_{HP,t}} = \sum_i \frac{L_{HP,i,t}}{\mathrm{L}_{HP,t}} \frac{K_{i,t}}{L_{HP,i,t}} \equiv \sum_i w_{i,t}^{KL} \, x_{i,t}^{KL}$$

where the weight $w_{i,t}^{KL}$ is given by the sector labor share within the economy.

Analogously, and in line with the standard approach in the literature (see for instance Baily, Hulten and Campbell, 1992), the index of aggregate TFP is defined as a geometric average of the sector-level TFP indexes, weighted using the real value added shares, which implies for the trend aggregate TFP that

$$x_t^{TFP} \equiv \log(TFP_{HP,t}) = \sum_i \frac{\tilde{Y}_{i,t}}{\tilde{Y}_t} tfp_{HP,i,t} \equiv \sum_i w_{i,t}^{TFP} \, x_{i,t}^{TFP}$$

where $w_{i,t}^{TFP}$ is the share of potential output of sector *i* at time *t*.

The aggregate variation $\Delta x_{t,0}^{j}$ of variable *j=KL,TFP* between time *t* and a reference year indexed by 0 can then be decomposed as follows:

$$\Delta x_{t,0}^{j} \equiv x_t^j - x_0^j = \sum_i w_{i,0}^{j} \, \Delta x_{i,t,0}^{j} + \sum_i \Delta w_{i,t,0}^{j} \, x_{i,0}^{j} + \sum_i \Delta w_{i,t,0}^{j} \, \Delta x_{i,t,0}^{j} \equiv WG_{t,0}^{j} + BG_{t,0}^{j} + CG_{t,0}^{j}$$

where $WG_{t,0}^{j}$ is the within sector component of growth, $BG_{t,0}^{j}$is the between sector term and $CG_{t,0}^{j}$ is the residual term measuring the interaction between the previous two components (cross term). We consider four time intervals (2001-04, 2005-08, 2009-13 and 2014-18). In order to make the figures for the cumulative changes comparable across the periods, we divide them by the length of the intervals, which is not constant.

Figure 7 shows the decomposition for the trend TFP growth: the average growth within each sector is what drives the aggregate dynamics. Both the within component and the aggregate TFP growth are negative until the end of the crisis. In the last period, this component turns positive and, together with a reallocation toward high productivity sectors, brings a positive TFP growth (around 0.5% per year).

Figure 7 – Decomposition of trend TFP growth

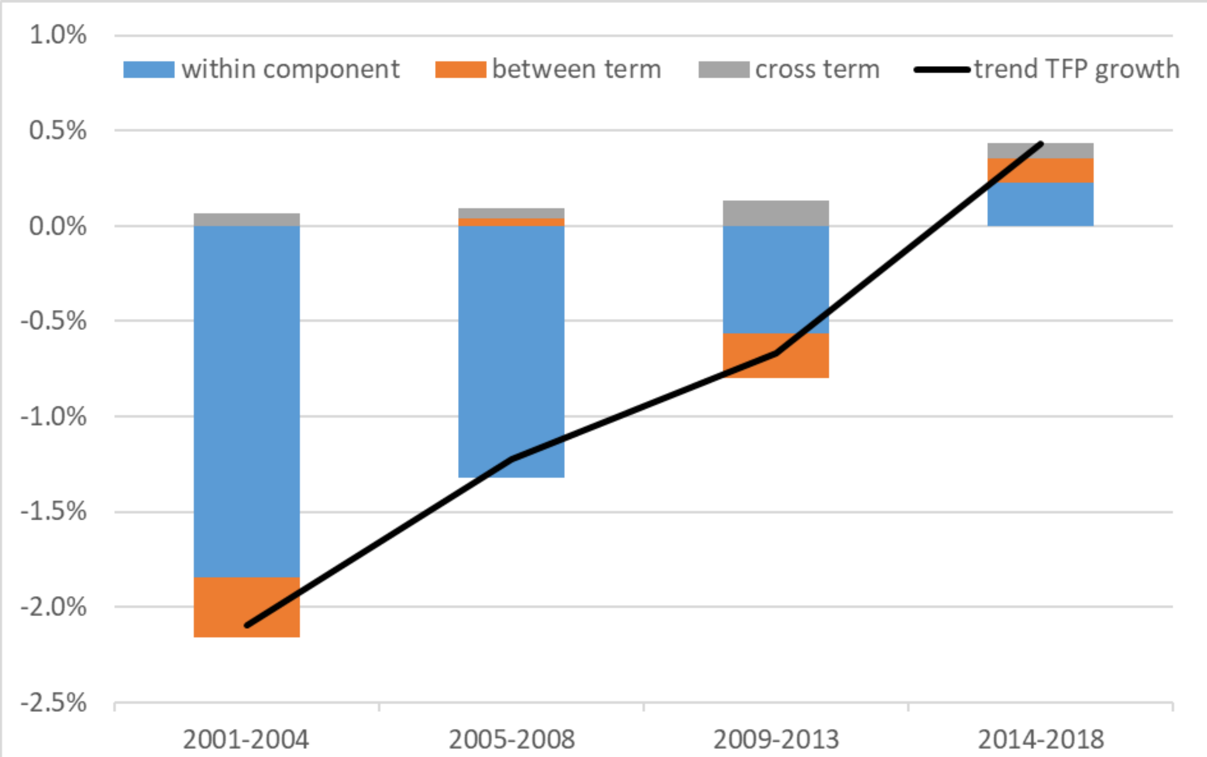


Figure 8 – Decomposition of trend capital labor ratio growth

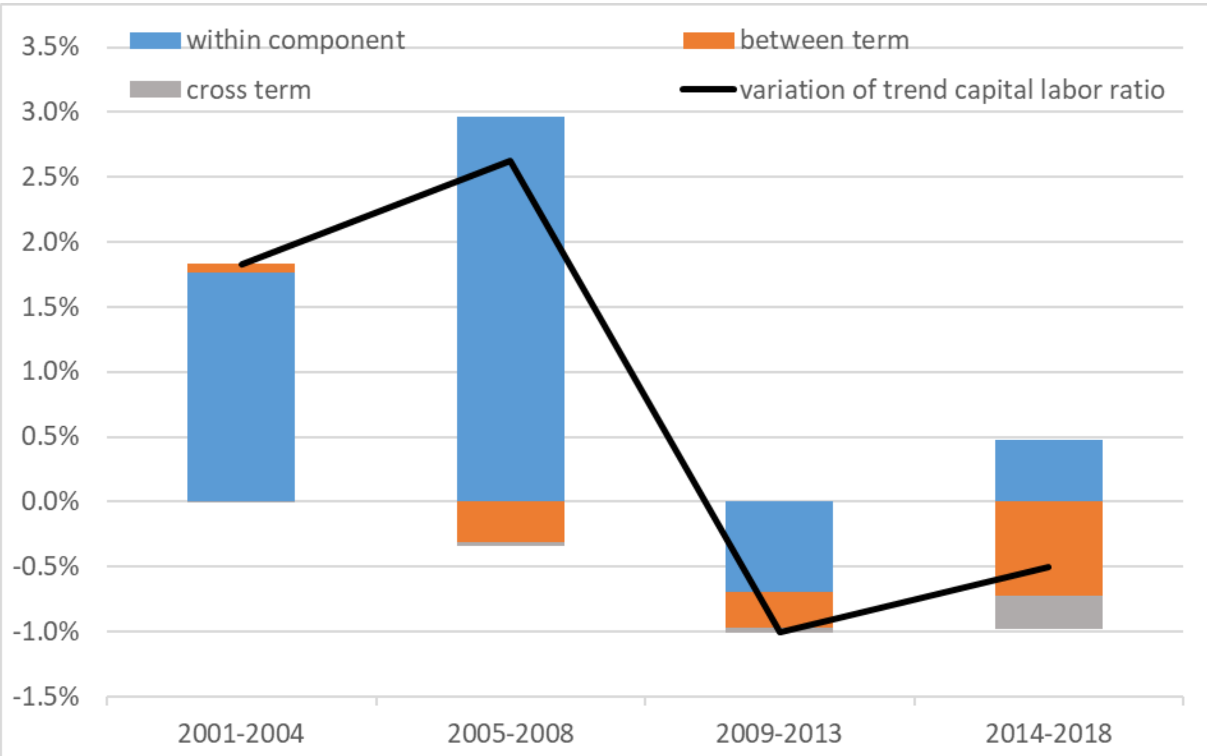


Figure 8 presents the dynamics of the trend capital labor ratio;[26] also for this variable there is a prevalence of the within component until 2013. The between and the cross term hold back capital accumulation in the last period instead: the ratio increases on average, but sectors with lower ratios at the beginning of the period (between component) or those with a decreasing ratio increase their share in the economy in terms of employment.

6. Robustness checks

In this section, we present several checks to confirm whether the results stemming from the directly aggregated potential output used as a baseline in the previous section are robust to changes in the methodology and the underlying data.

First, we check whether the methodological tools (weights and imputations) that we used to improve the representativeness of our sample of firms have an impact on the estimated dynamics of potential output. Figure 9 compares our baseline, already shown in Figure 3, with the one obtained ignoring the weights and the one based on the raw dataset where neither weights nor interpolations are used. Estimates are qualitatively similar, but our baseline is a bit more pessimistic in several years including the most recent ones, plausibly because in the raw dataset some segments of the economy, such as small mature firms active in services - whose contribution to potential output is weaker - are underrepresented.

A second set of robustness checks regards the calculation of capital. national accounts define sectoral depreciation as the share of value lost by physical capital during the year due to wear and tear, obsolescence and accidental damage; capital older than a threshold age is assumed to be dismissed. Hence, there may be a double counting in the calculation of the permanent inventory capital between sectoral depreciation and firm-level divestments. To take care of this, we conservatively calculated an alternative amount of capital gross of firm-level divestments (K_{it}^{PI2}, equation [1]). Depreciation and divestment implied by this definition are by construction systematically lower than those in our standard case; indeed, the two estimates are respectively a lower and an upper bound of the true value consistent with the definition of the national accounts. Figure 10 shows the results using the alternative definition of capital: the overall dynamics of potential output is substantially unchanged.

[26] In the figure, the change in the capital labor ratio, as well as all its components, are normalized as a percentage of the ratio in the base year of each interval ($\frac{K_0}{L_{HP,0}}$).

Figure 9 – Robustness checks, treatment of sample

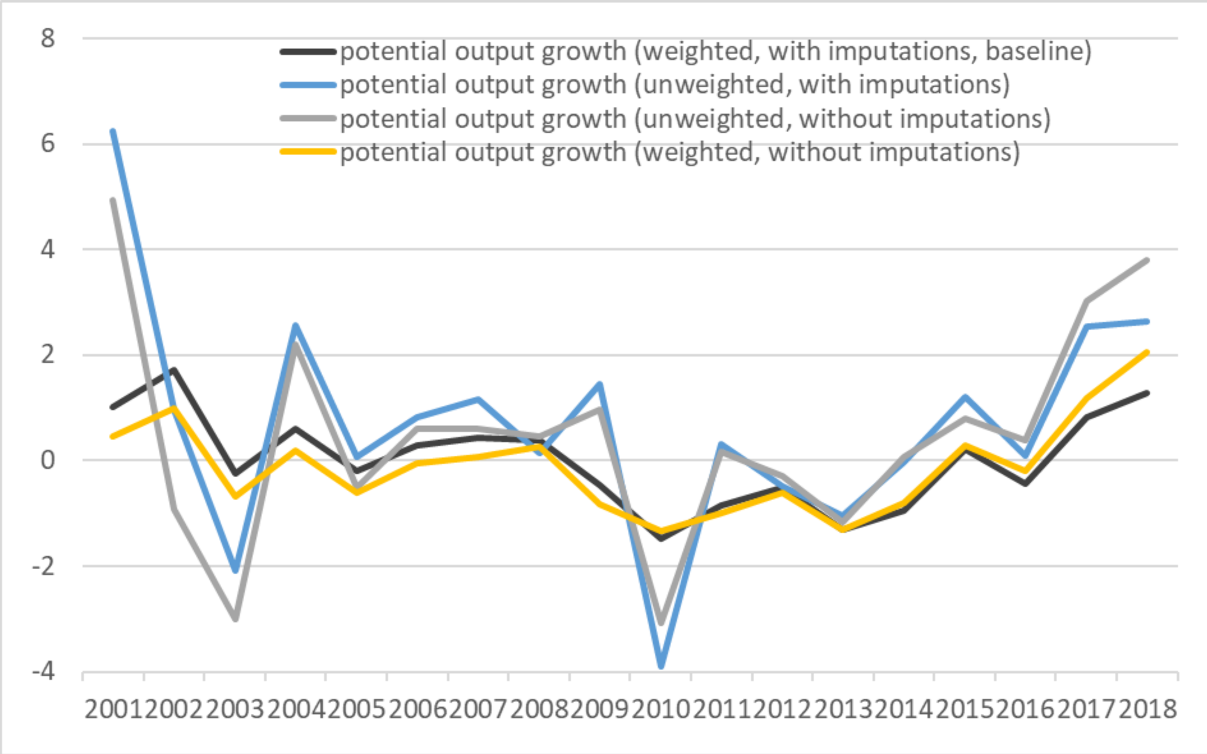
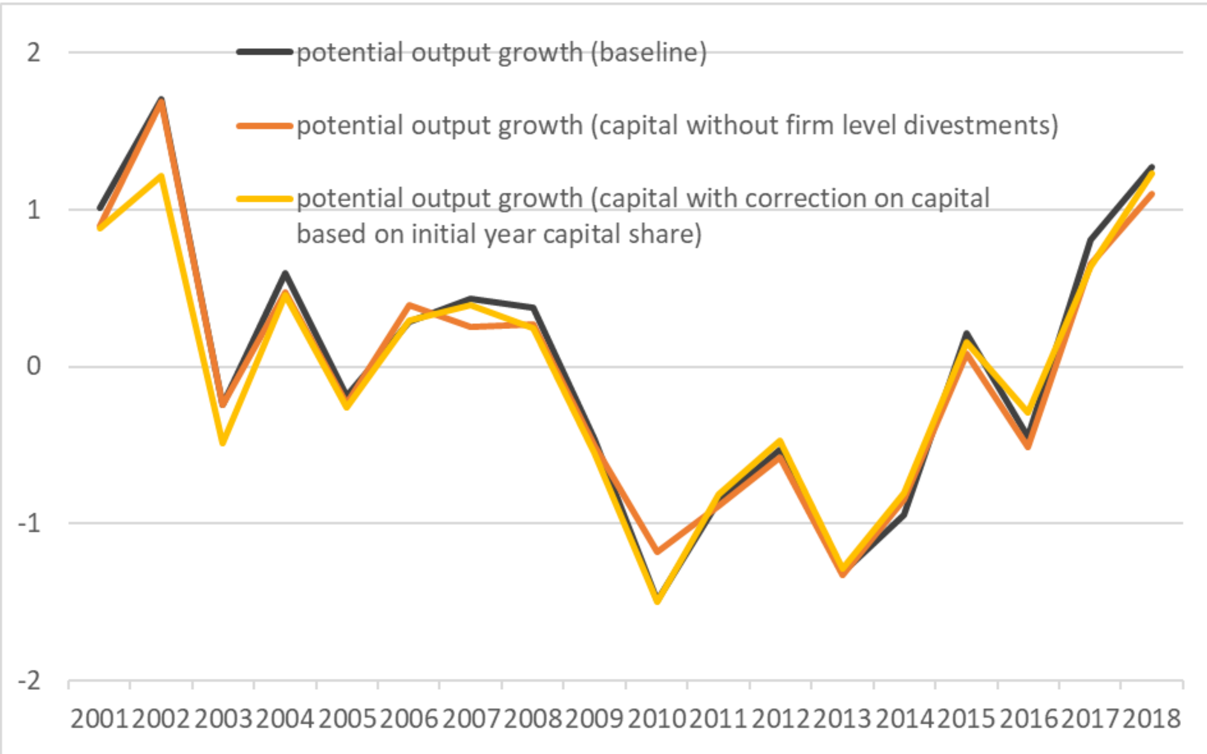


Figure 10 – Robustness checks, capital



Another element that merits attention in the construction of the capital is that the permanent inventory method cannot be used to estimate the value of the capital in the initial year of the time series of each firm. While this is not an issue with newborn firms, because we observe them since their infancy when little capital was accumulated, it can be a source of bias with firms who entered the market well before the beginning of our sample. For this reason, even if we use the available balance sheets since 1995 to construct capital, we observe the behavior of firms only since 2000: after 5 years, most of the impact of the initial conditions should fade away. Anyway, as an additional robustness check, we rescale the amount of capital for each firm existing in 1995 in such a way that the shares of capital in each sector in our sample exactly mimic those reported in the national accounts. Figure 10 also shows the results following this additional correction; there is a small effect on potential growth in the first few years, but the overall dynamics do not change.

In a third set of robustness checks, we introduce few methodological changes. First, we indirectly aggregate potential output, splitting the sample in the first step by sector of economic activity and then aggregating the different sectors using a Tornqvist quantity index methodology (equation [5]). Second, we use the sectoral labor income shares from the national accounts, reported in Table 2, to calibrate the parameter α of the Cobb Douglas production function, instead of those calculated within our sample. On the one hand, the national accounts are more comprehensive than sample based data, because they are calculated on the universe of firms; on the other hand, they include categories of firms such as partnerships excluded from our dataset and therefore can be less accurate in the description of our firms. Figure 11 reports the results; both robustness checks confirm our previous results.

In the last robustness check, we introduce a trend elasticity of substitution between the inputs that is not only sector- but also time-specific: we calibrate parameter α of the Cobb Douglas production function using the 5-years moving average income shares of labor calculated in our sample shown in the bottom half of Table 2. Figure 12 presents the impact of this source of heterogeneity on potential growth: the overall dynamics of potential output are qualitatively the same, but all the variations are strongly magnified. This greater overall cyclicality is not a desirable property for potential output. This result is probably due to the existence of correlation between potential growth and the dynamics of the input shares, which partially reintroduce cyclicality in the estimated time series.

Figure 11 – Robustness checks, methodological checks

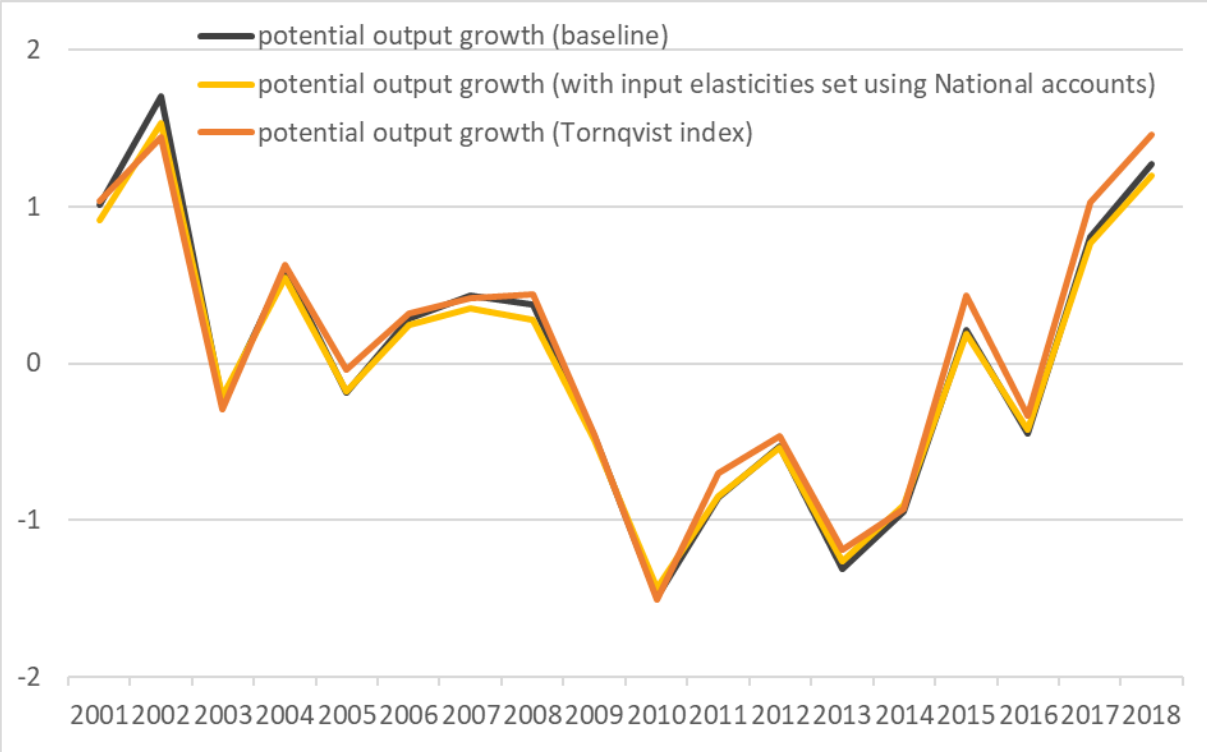
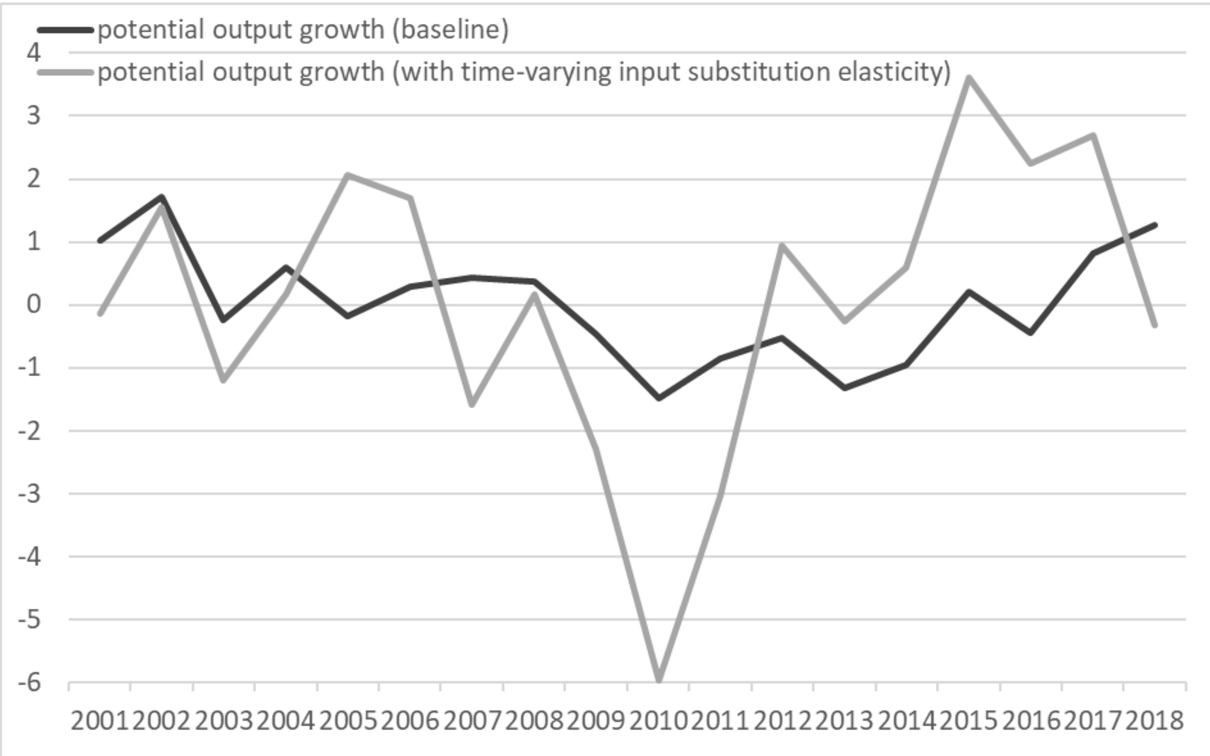


Figure 12 – Robustness checks, time-varying input elasticity of substitution



7. Conclusions

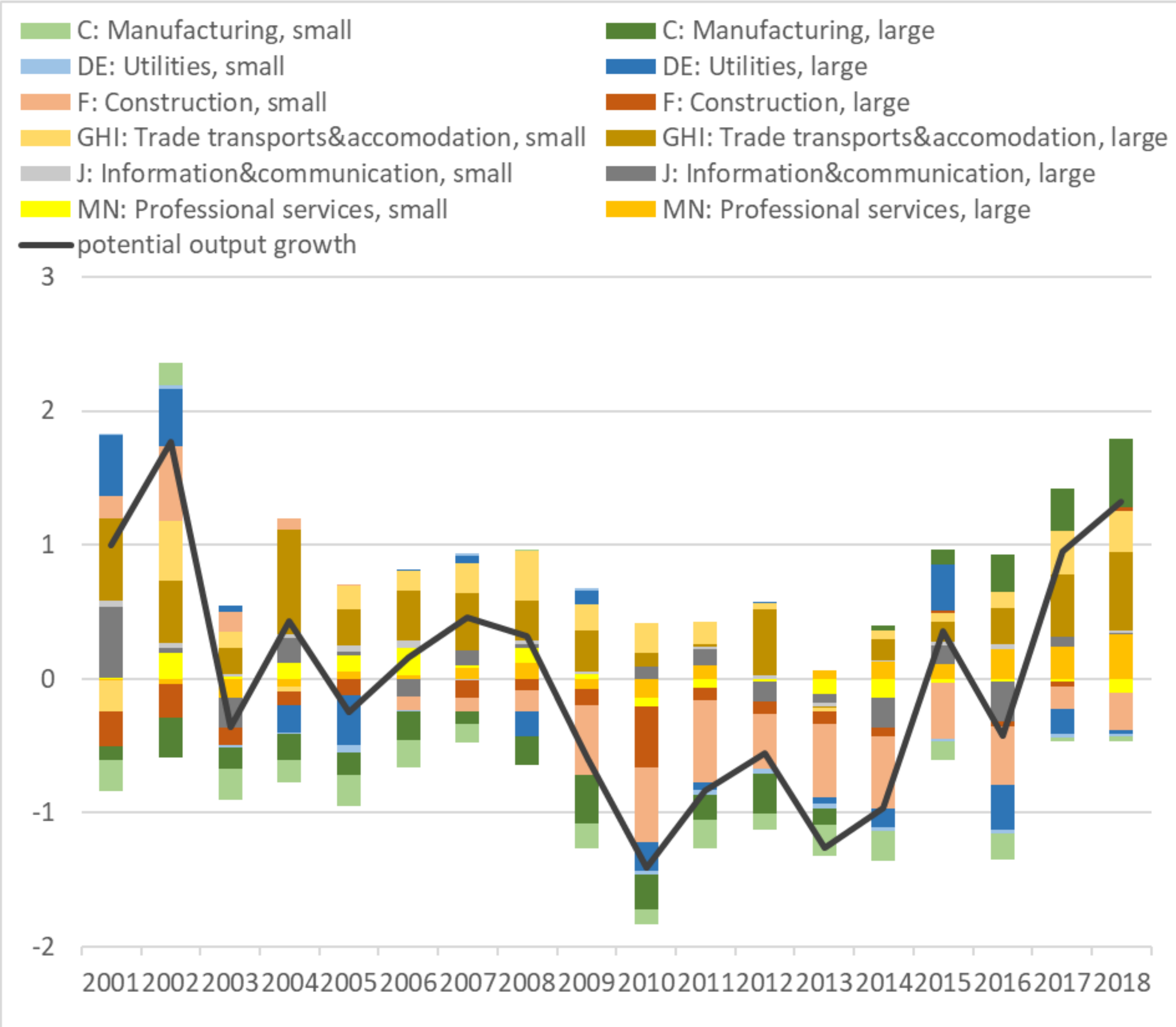
In this paper, we applied a growth accounting method to aggregate statistics from a very rich firm-level dataset for the period 2000-18. Our approach is similar to the production function methodology for potential output estimation traditionally used at the Bank of Italy and described in Bassanetti *et al.* (2010). The aim of our work is to exploit the information available from a micro-dataset to shed light on the heterogeneity below the dynamics we observe for aggregate potential output. Being able to assess which firm characteristics are more associated with higher potential output growth can be useful for the design of the most effective economic policies to ensure economic growth.

We find that the dynamics of potential output come mainly from small firms that contributed positively before the Great Recession, and, due to their structural weakness, negatively afterwards. Younger companies, which are probably more dynamic and innovative, always provide a positive contribution to potential output growth. Due to a lack of selection mechanisms, firms in Italy tend to survive and grow old even when not productive and, as a result, we find that older firms always make a negative contribution to growth. At the sectoral level, manufacturing and construction reduced their contributions to potential output, but, differently from other countries, this did not correspond to an increased share of high-tech knowledge-intensive services, whose contribution has been mostly negative. Looking at the location of firms in terms of the macro-areas, the contribution of those from the North-West and Central Italy become strongly negative during the double recession. The recovery in more recent years gradually concerns all the geographical areas, even if the contribution of the South and Islands is weak; it is particularly robust instead in the North-East. Last, we show that growth within sectors is the main driver of the dynamics of both aggregate trend TFP and capital labor ratio. Since 2014, though, sectors with lower capital deepening have increased their share in the economy, holding back the aggregate figures.

Appendix A – Additional results

In this appendix, we show some additional results based on the partition of the dataset according to other firms characteristics; we consider a joint decomposition of size and sector of economic activity, then we analyze capital, technological and knowledge intensity.

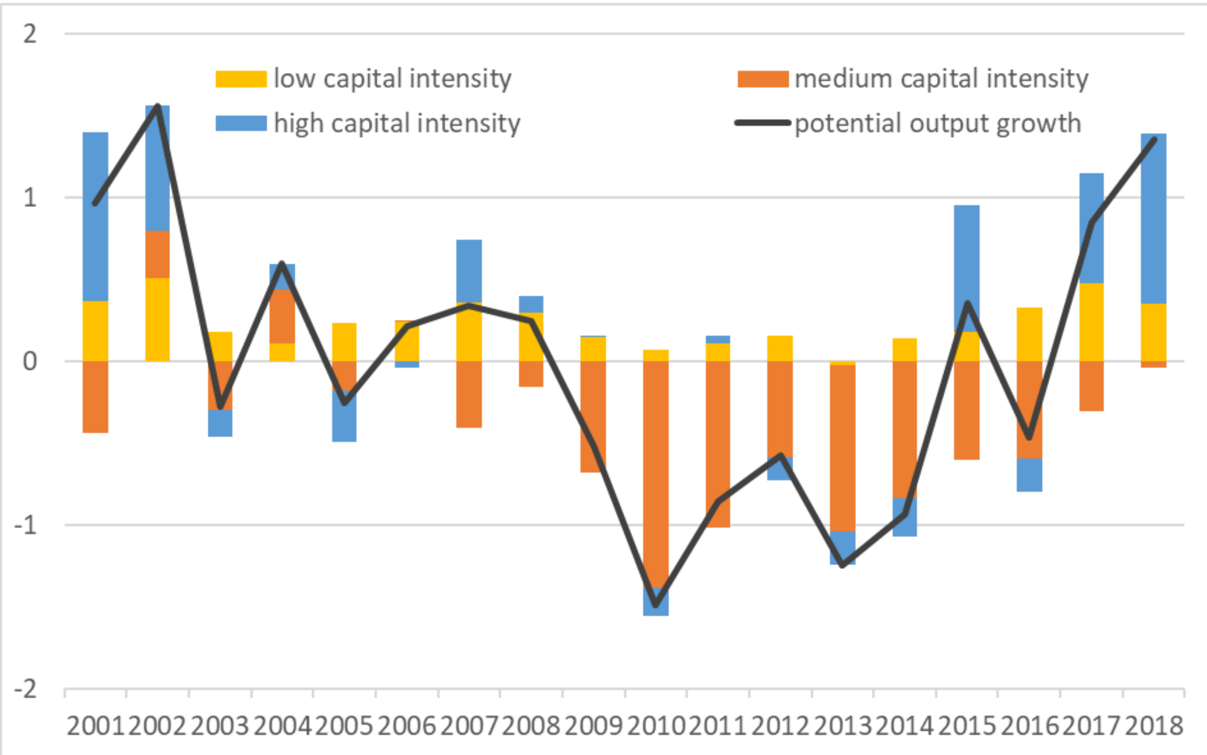
Figure A1 – Potential output growth, by economic sector and firm size



In a first exercise, we jointly consider size (two categories: up to 20 and more than 20 employees) and sector of economic activity. Figure A1 shows the results, which for the most part confirm what shown in section 4. On the one hand, services play an important role to sustain potential output dynamics between 2001 and 2018. Firms in commercial and touristic services (G-I) are the main driver of growth in the whole period, with a positive and strong contribution in all years but 2013; within this sector, large firms contribute almost twice the smallest ones. A positive but lower contribution also comes from large professional activities (M-N). Large firms in information and communication services (J) provide a positive contribution in the first part of the period, but the impact of the crisis is strong and more long-lasting. On the other hand, the construction sector (F) provides the most negative contribution over the whole time window, especially since the double-dip recession; the level of activity is still nowadays very far from its pre-crisis level. Manufacturing firms (C) provide a negative contribution to potential output growth until 2015, following the slow process of gradual expansion of the services industry in the economy and the increased competition on international markets; their contribution becomes positive later, but only for large firms.

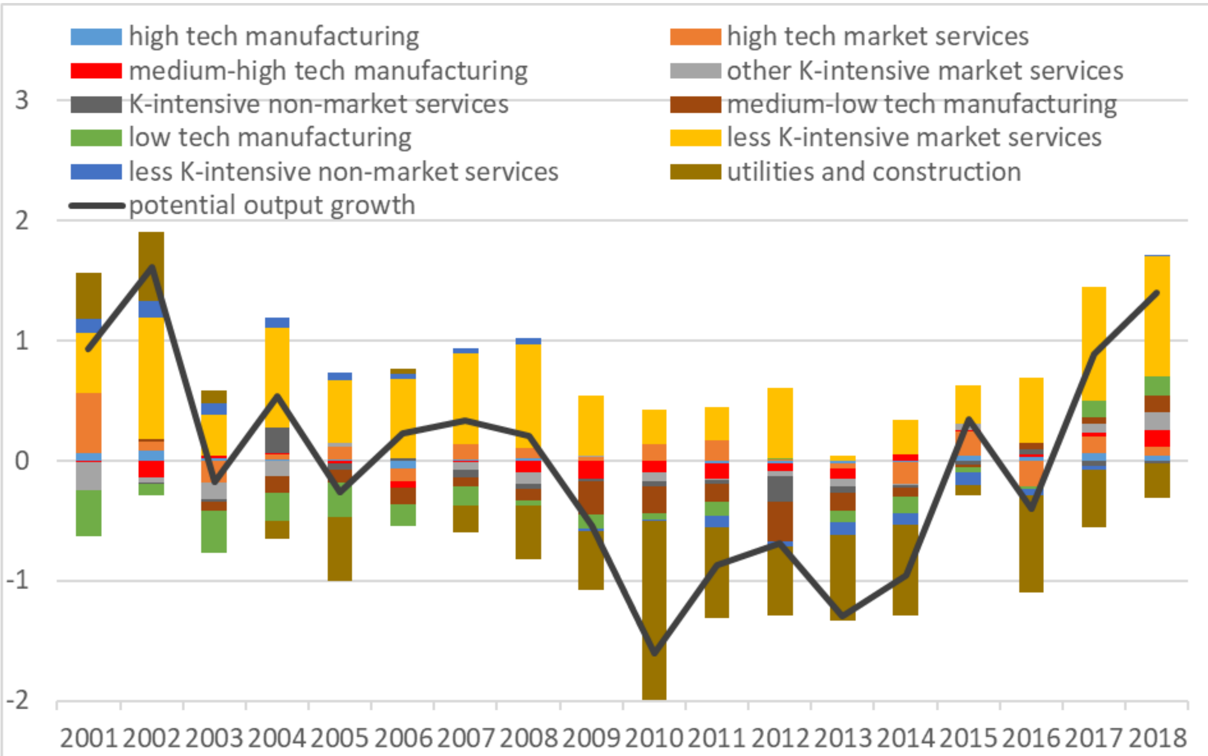
In a second exercise we group firms by capital intensity, defined as the ratio, averaged over the period considered, between the income shares of capital and labor for each sector in the dataset. We split the sample in three groups, including in each one third of the firms in the distribution of the ratio. Figure A2 shows the results: sectors with the lowest relative level of capital give a positive contribution in substantially all the years, reflecting the relevance of services sectors already discussed. Conversely, sectors with high intensity provide a negative contribution in several years, especially those with a negative contribution of capital accumulation, but they become the most relevant driver of growth in the recent recovery. Medium intensity sectors, where the bad performance of construction is only partially compensated by the one of commercial services, are the most affected by the double-dip crisis.

Figure A2 – Potential output growth, by capital intensity



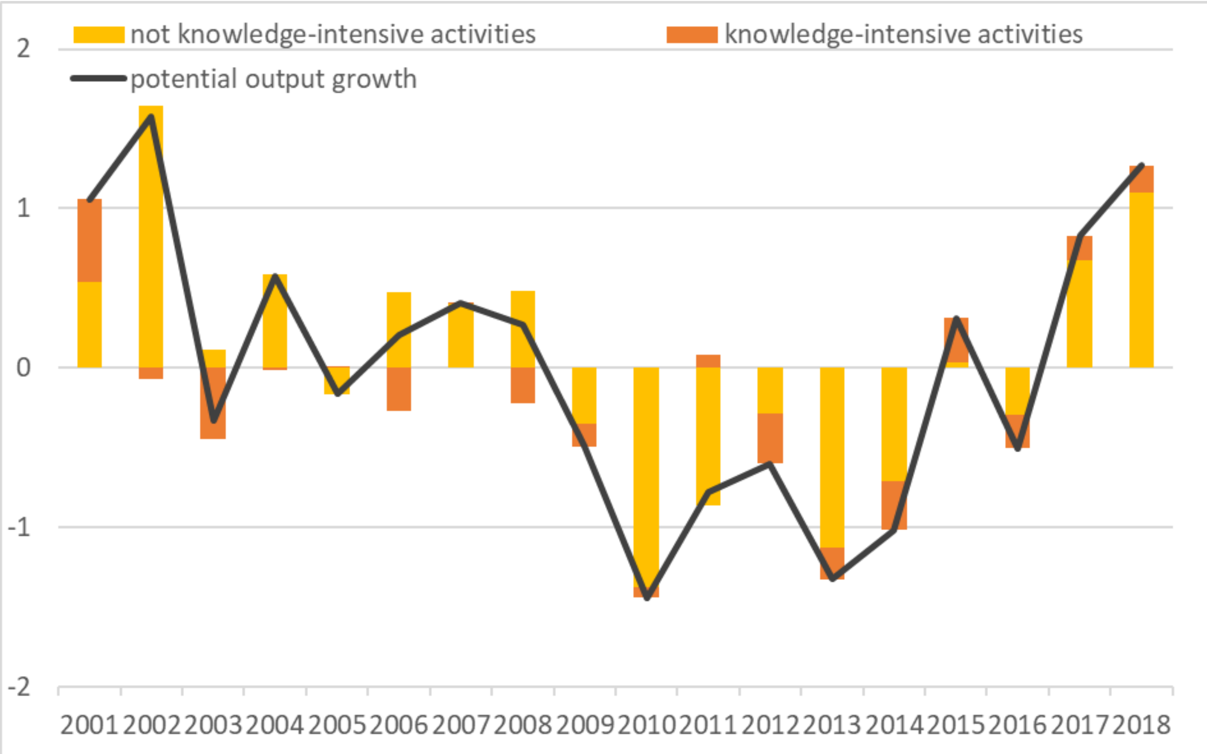
In the last two exercises, we use instead two different Eurostat classifications to evaluate the role of R&D and knowledge on potential output dynamics (Eurostat, 2016). In the first one, manufacturing sectors are classified at two-digit level in four different categories of technological intensity (high, medium-high, medium-low and low tech) according to their ratio between R&D expenditure and value added. Following a similar approach, also market and non-market services at the same level of detail are separately classified in high tech (market only), knowledge-intensive services and less knowledge intensive services. Utilities and construction sectors are not classified. Figure A3 shows the results for this exercise: less knowledge intensive market sectors drive the growth of potential output in all the years; the contribution of high tech services is generally positive, but smaller. All the categories of manufacturing slowdown potential growth during the crisis; in particular, the low tech segment negatively contributes until 2015.

Figure A3 – Potential output growth, by technological intensity



In the second classification, industries with the higher share of tertiary educated workers are named as knowledge-intensive activities. Figure A4 shows the results; in line with findings by sectors, and in particular the relevance of firms in commercial and touristic services, the contribution of low knowledge-intensive activities is generally predominant. Anyway, the overall dynamics is similar for both groups.

Figure A4 – Potential output growth, by knowledge intensity



Appendix B – Comparison with measures of potential output growth for Italy of the main international institutions

In this appendix, we compare our measure of potential output growth for Italy with those published by the main international institutions (European Commission, IMF, OECD). From a methodological point of view, all the estimates follow a production function approach and are therefore conceptually similar;[27] we summarize here the most relevant differences, mainly regarding the underlying data and how the trend values of the inputs are calculated:[28,29]

1. Data: the estimates published by the international institutions are based on aggregate macroeconomic time series from national accounts; instead, those proposed in this work exploit firm-level data, which do not include information about some sectors of economic activity, such as agriculture, mining, financial, real estate services, broad public and household services.
2. Trend total factor productivity: our paper, the IMF and the OECD use the trend Solow residual of the aggregate production function; instead, the European Commission uses a bivariate Kalman filter on the Solow residual and a capacity utilization composite indicator, calculated combining capacity utilization and economic sentiment indexes from the European Commission's Business and Consumer Survey Programme.[30]
3. Trend labor: our paper uses the trend in the overall number of workers of the firms included in the dataset; the European Commission, the IMF and the OECD construct trend labor input L_t^* as the trend in the total number of hours worked, defined as:

$$L_t^* = W_t P_t^* (1 - U_t^*) h_t^*$$

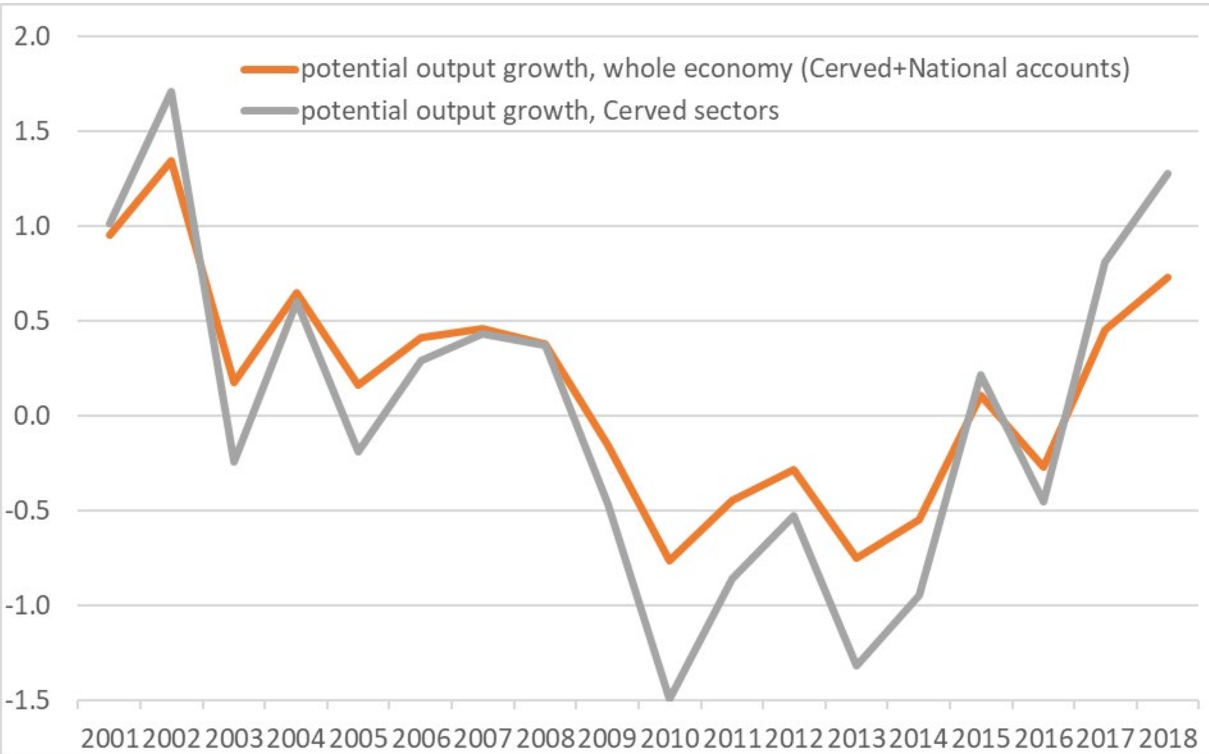
where W_t is the actual working age population, P_t^* is the trend participation rate and h_t^* is the trend average number of hours worked per employee; U_t^* is the trend unemployment rate, calculated to be consistent with a stable non-accelerating wage inflation (NAWRU) in the case of European Commission and IMF and with a stable non-accelerating consumer inflation (NAIRU) in the case of OECD.[31]

[27] See Havik *et al.* (2014) for the European Commission, De Masi (1997) for the IMF, Chalaux and Guillemette (2019) for the OECD.
[28] Where not specified otherwise, trend values are calculated with filtering procedures, typically using a Hodrick-Prescott filter.
[29] There are also minor differences in the values used to calibrate the parameters of the production function.
[30] See Havik *et al.* (2014) for details about the construction of the composite index and European Commission (2020) for details about the survey.
[31] See Havik *et al.* (2014), De Masi (1997) and Chalaux and Guillemette (2019) for the details of the specific models used in the construction of U_t^*.

4. Capital: in all cases, capital is constructed adding current unfiltered investments to the non-depreciated capital from the previous period, following a permanent inventory methodology. Our paper uses the aggregated firm-level material and immaterial investments and disinvestments declared in the balance sheets. The European Commission and the IMF use aggregate net total investments. The OECD uses a concept of productive capital stock, constructed from non-residential net investments taking into account the gradual loss of productive efficiency of the vintages.

To ease the comparison between our potential output growth estimates and those of the international institutions, we use aggregate macroeconomic time series for the sectors not included in our dataset to improve the representativeness of our estimates at the level of whole economy. In detail, here our potential output growth is a weighted average of the estimates from the main section of this work and of the growth rate of the trend value added of the excluded sectors, extracted using a Hodrick-Prescott filter on the sectoral time series from the national accounts.[32] The dynamic of our measure for the whole economy is qualitatively similar to the one proposed in the main text of the present work; the inclusion of the additional sectors, in particular the public one, reduces its cyclicality (Figure B1).

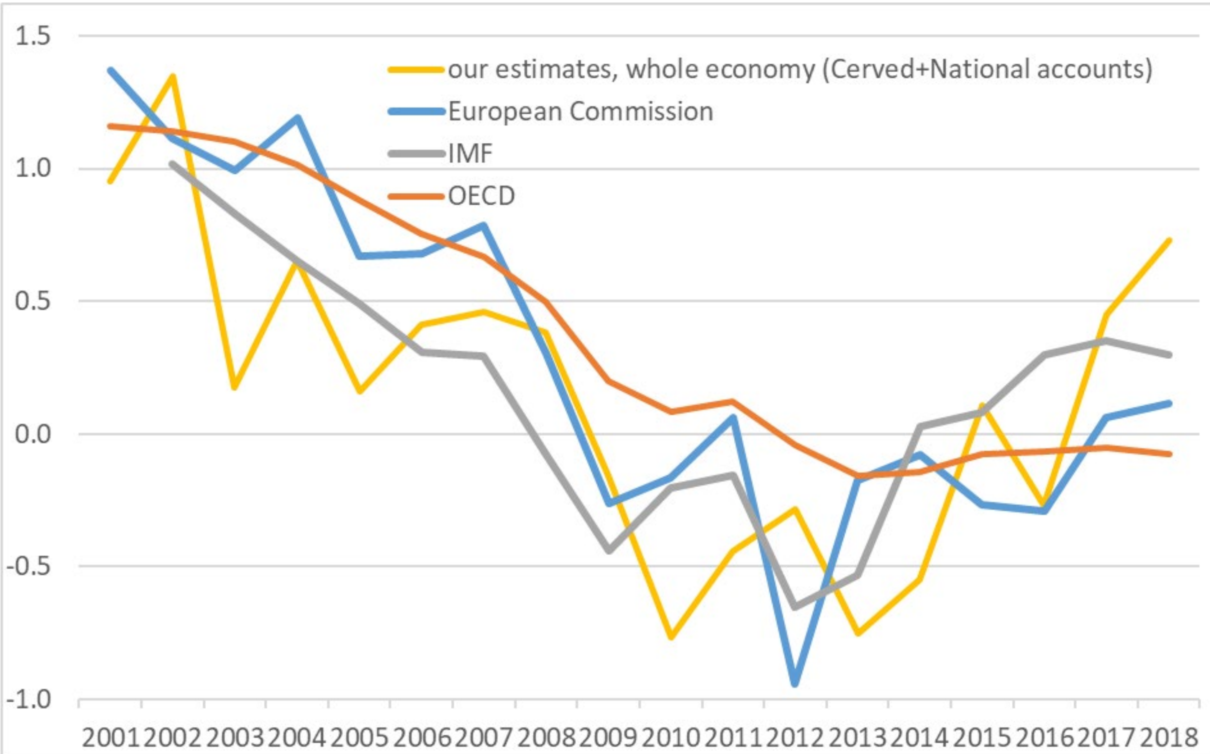
Figure B1 – Potential output growth, Cerved sectors and whole economy



[32] The two components are weighted using the sectoral shares of value added from the national accounts.

Figure B2 shows our modified measure of potential output growth and those estimated by the main international institutions; all the estimates broadly share similar dynamics. Potential output growth was around 1% before the great financial crisis. It gradually declined and became negative during the double dip recession: the average contraction between 2009 and 2014 is about 0.5% according to our estimates, 0.3% for the IMF and the European Commission and 0.1% for the OECD. Finally, in the most recent period the recovery is stronger for the IMF and for our estimates, while it is slower and close to stagnation for the OECD and the European Commission.

Figure B2 – Potential output growth, comparison of estimates



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